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Willingness Impact to the PAR Optimisation of R-users Community using EMS

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Abstract

The optimisation of residential users' power usage is measured by Peak-to-Average (PAR) ratio. Higher PAR leads to increase in the cost for both power suppliers and residential users. Suppliers use expensive resources during these peaks, in turn, the residential users will pay more during these times even for the same amount per kW/h. The aim of this study is to investigate the use of an energy management algorithm within an Energy Management System (EMS) to optimise power consumption and to reduce the overall PAR for a community of users. Beyond the group optimisation, the algorithm takes into account the heterogeneous nature of the community by introducing individual household values of willingness to save power and have the energy managed. In conjunction with the concept of community energy management and willingness, the paper also highlights the importance of incentives for power load optimisation to each user. The proposed algorithm is tested on 15 R-users load profiles, selected based on criteria such as house size, temperature level, by measuring the load of each individual user profile during a 24-hour cycle with a 10-minute resolution. The results show that the algorithm provides a 22.66% reduction of the PAR was 22.66% in a multi-user scenario. Other aspects that could influence the PAR reduction are measured, such as the impact of PAR optimisation by individual R-users without considering the community and the impact of different R-users willingness to use the proposed EMS. This indicates that the effective proposed EMS optimisation is significantly accepted at the point of applying it in single and multi-users scenarios in spite of the variance accepted level of these R-users being considered.

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1. Introduction

Electricity power generators are facing several environmental and utility management challenges. One of the recently proposed alternatives to overcome these challenges is to create an intelligent power grid, able to communicate across its infrastructure, from producer to consumer, also known as a Smart Grid (SG). Energy consumption of a residential and commercial sector has significantly increased in developed countries [1]. It is difficult for the residential users (R-users) to manually optimise their consumption hour by hour [2] [3] [4]. This difficulty for users to optimise their power usage is caused by a lack of required knowledge and time to meet a multiplicity of decision parameters, constraints involved, and possible variations of these parameters over time [2]. To support the end-user energy consumption, the concept of Energy Management System (EMS) was proposed as a solution to implement optimization algorithms that can the power usage of residential users' (R-users) [4,5]. A number of alternative mechanisms, such as Demand-Side Management (DSM), Demand Response (DR), and Home Energy Management (HEMSs), have been developed [6]. However, regarding practical scenarios, little attention has been paid to taking into account of general uncertainties in the conditions of users, such as uncertain user load [7], user preference [8] [9] [3], and the willingness of users to respond.

The purpose of this study is to describe and examine an EMS algorithm with consideration of the community-based DSM. This paper aims to conduct the premise that the end-user has different preferences which could vary based on various factors, such as time of day, real-time price, users' motivation level for environmentally friendly conditions, customers' revenue, lifestyle to name just a few. In order to demonstrate a practical study, real data of power usage for R-users is considered. Moreover, an appliance-by-appliance level of control, based on users' willingness, has been applied. The comparison results of single R-users and community-based solutions are presented in both scenarios with and without considering R-users' willingness.

2. Literature review

In order to produce a practical solution for optimising power usage, user satisfaction needs to be considered in the wider context of user willingness. In terms of user willingness, every R-user has various preferences, appliances, comfort, willingness to save energy such as cost or/and environmentally friendly conditions, and so on. Liu et al., (2014)highlighted the fact that different users having different preferences is still an open issue [9]. Khadgi et al., (2015) argued that many end-users prefer to use electricity even during the expensive time [10]. Therefore, they suggested an Agent-Based System (ABS) for managing each individual user's needs depending on whether they have a high-, medium-, or low-income. This ABS is responsible for maximising the utility function, which is computed by a trade-off between cost and convenience. The convenience factor was assumed as fixed hours of power usage during evening and morning times. Similarly, Zhu et al., (2011) applied the concept of fixed hours as users' preferences, then formulated a new user's preferences model but with more details of individual appliances [11]. A manual response of users to satisfy their willingness and optimise the power usage could lead to shifting the load from a typical peak time slot to a non-peak time slot without optimising the power load [12] [2] [4]. The significant impact of users' willingness for designing a more efficient power usage management system has been studied by Soares et al., (2014) [2]. The latter analysed the balance between EMSs' optimisation levels and the users' willingness to accept an automated system to control the power consumption of individual appliances. Recently, Shin et al., (2017) proposed an appliance scheduling methodology for EMS by considering the discomfort index [4]. Despite the research towards considering users' willingness, there remains a need for an efficient method that conducts variable convenience, practical numerical optimisation methods, and a community aspect solution. While the users' preferences were considered in previous work, the drawback of fixed convenience is inefficient for a practical solution. Set specific preference times for all users by Khadgi et al., (2015) [10] or specific power preferences by Zhu et al., (2011) [11] are far from practical users' preferences. Regarding the community-based solution for power optimisation, few researchers have addressed the problem of the community for optimisation power usage. Zhu et al., (2011) observed the possibility of applying the energy management for neighbourhood/local areas for achieving a centralised load management [11]. In addition, Mohsenian-Rad et al., (2010) attempted to develop the community-based solution by adding a message exchange between users [12]. However, the research showed there is an absence of a community-based solution incorporating users' willingness.

This paper has been divided into three parts. The first part deals with the proposed system's architecture and requirements. The second part shows the methodology that has been followed to experiment and results of experimenting on the proposed system. Finally, the findings and implications of the results are presented in the conclusion.

3. Proposed system

As acknowledged by previous research, the issue of PAR and community energy saving are critical in the context of reducing energy costs and associated impact on the suppliers. This paper considers a smart community system composed of multiple residential users (R-users) and a community-based server. This system applied a harmonious energy management between the individual R-users EMS and community-based EMS, which will lead to increase the satisfaction of both sides in terms of cost and convenience. The system is equipped with two-way communication that enables the system's components to exchange information with each other. S.G is used to connect R-users with the community server. Assuming every user supported by a HEMS [4], this HEMS could be utilised to provide the community server with users' willingness values at each given time. These values reflect the incentive level of the power load optimisation to each user to allow an automatic system to control the users' power usage.

With respect to general user load types, each user has shiftable and non-shiftable loads depending on their appliance types. The willingness value that is provided by individual HEMS will influence only the shiftable load. For example, if there are three users, user-1, user-2, and user-3 with willingness values 0, 1, and 0.7 respectively; it means that user-1 has no willingness which in turn, there is no allowance for the community sever to influence any load for this user. User-2 allows the community server to fully control all of the shiftable load when there is a high power usage at each time of a day. User-3 with willingness 0.7 means that the user allows only 0.7 of his/her shiftable load to be controlled by the community sever. The proposed community_based EMS applied varied controlling decisions based on the user's willingness. It is noteworthy to mention that, in addition to each user having a different willingness value, the individual user's response, from a practical perspective, is different depending on their comfort level linked to each individual appliance. For instance, although two users have the same willingness values for example 0.5 that means the community sever has affected only the half of the shiftable load of each appliance each user might choose different shiftable appliances. For example, one of them prefers shifting the power usage of dryer machine and washing machine, while, another prefers shifting the power usage of dishwasher and A/C. The proposed algorithm that runs in the community server considered the effect of the willingness values on an appliance-by-appliance level of individual users. Furthermore, the shiftable appliances preference of individual users might vary from one time to another; for example, the users' preferences vary between working days and weekends or between summer and winter. Therefore, a satisfied information exchange between the HEMS and community server is crucial. In order to obtain the optimal scheduling, whilst considering the user satisfaction, the following Pseudocode was proposed:

Pseudo code: the optimal scheduling with considering the user satisfaction

Let N users, M_n number of appliances for n user, s_n shiftable appliances for n user, i_n essential appliances for n user, $x_{n,s}$ scheduling vector for shiftable appliances, $x_{n,i}$ consumption scheduling vector for non-shiftable appliances, t given time, $t \geq 00{:}00, and\ t \leq T$, $T = 23{:}50$, ct current time slot, $Dataset\_Hist$ historical data set, $Dataset\_Updated$ optimized power usage dataset, W_n Willingness value of user n, Na_SHF_Req number of shifting requests, $Na\_allowed\_Req$ number of allowed shifting requests based on the willingness value, $Apply\_SHF\_List$ list of selected shiftable appliances which the user chosen to be shifted.

Initialise parameters (W_n, , $Agg\_Load_t = \sum_{n=1}^{n=N} l_n^t$, while $l_n^t \triangleq \sum_{i,s \in M} x_{n,i}^t + x_{n,s}^t$, $AVL\_Hist = mean(\sum_t^T(Agg\_Load_t))$, WHILE l_n^t used in AVL_Hist based on Dataset_Hist.

REPEAT
 IF ($Agg\_Load_{ct} > AVL\_Hist$)
  THEN
   // the Agg_Load_j calculated by Dataset_Updated

```
            Offpeak_val = Agg_Load_ct
            FOR (j = ct, j < T, j++)
                    IF(Agg_Load_j < Offpeak_val)
                    THEN
                            Offpeak_val = Agg_Load_j
                            Offpeak_slot = j
                    ENDIF
            ENDFOR
       FOR(n = 1, n < N, n++)
            IF(W_n > 0)
            THEN
                    Na_SHF_Req = length(x^ct_n,s) // for each [x^ct_n,s] > 0
                    Na_allowed_Req = W_n * Na_SHF_Req
                    Apply_SHF_List = Random.Select(x^ct_n,s, Na_allowed_Req)
                    FOR (k = 1, k < Na_allowed_Req, k++)
                            Predicted_Agg_Load = Agg_Load_Offpeak_slot + Apply_SHF_List[k]
                            IF (Predicted_Agg_Load < AVL_Hist )
                            THEN
                                    Dataset_Updated[Apply_SHF_List[k].row, offpeak_slot]
                                    =
                                    Dataset_Updated[Apply_SHF_List[k].row, offpeak_slot]
                                    + Dataset_Updated [Apply_SHF_List[k].row, ct]
                                    Dataset_Updated [Apply_SHF_List[k].row, ct] = 0
                            ELSE
                                            Offpeak_val = Agg_Load_ct
                                    // find another possible off peak
                                    FOR (j = ct, j < T, j++)
                                            IF(Agg_Load_j < Offpeak_val)
                                            THEN
                                                    Offpeak_val = Agg_Load_j
                                                    Offpeak_slot = j
                                            ENDIF
                                    ENDFOR
                                    IF (Predicted_Agg_Load < AVL_Hist )
                                    THEN
                                            Dataset_Updated[
                                            Apply_SHF_List[k].row, offpeak_slot] =
                                            Dataset_Updated[
                                            Apply_SHF_List[k].row, offpeak_slot]+
                                            Dataset_Updated [Apply_SHF_List[k].row, ct]
                                            Dataset_Updated [Apply_SHF_List[k].row, ct]
                                            = 0

                                    ELSE
                                            Unresponse_SHF_Req++
                            ENDIF
                    ENDFOR
            ENDIF
       ENDFOR
   ENDIF
UNTIL (Agg_Load_t) = ∅// there is no load by users
```

4. Results

It is known from the literature that the PAR reduction leads to efficient electric usage of power systems [2]. In general, EMS could be run to optimise the power usage of individual R-users or multi- R-users [5]. In this section, the proposed EMS algorithm was evaluated for PAR reduction in several aspects; single user scenario, multi-user scenario, single user scenario with considering user's willingness, and multi-users with considering users' willingness. These several aspects of evaluating the proposed EMS are applied to demonstrate the effectiveness of the EMS in variant scenarios, in order to conclude the preferred life circumstances for a better PAR reduction. In this work, the users' power usage profiles were loaded from the dataset which provided by Cambridge Architectural Research (CAR) and the Department of Energy & Climate Change (DECC) in U.K[13]. A total of 15 samples of users profiles were grouped for performance analysis of the proposed EMS algorithm which was mentioned earlier. The selection of user profiles was consistent in terms of time of the year, to ensure the results are meaningful. A load of each individual user's profile is measured during a 24-hour cycle with 10 minutes resolution. There are 11 types of appliances which were measured at each time slot of 10 minutes. Regarding the user willingness, these willingness values have been randomly applied to these users. The output results show the optimisation average of the load consumption by PAR reduction was 12.31%, 22.66%, 10.34%, and 16.25% of the single user scenario, multi-user scenario, single user scenario with considering user's willingness, and multi-users with considering users' willingness, respectively as explained in Table 1. The output results of 15 R-users in single and multi_users indicate that the new power load consumption has been optimised compared to the original power usage. The EMS in a community-based optimisation has better performance than in the single users' scenario.

Table 1 The comparison of the PAR optimisation with and without willingness with taking into account the single and community-based solution

Willingness average	PAR initial	PAR_optimised in single –user scenario	PAR_optimised in multi-users scenario	Optimised percentages in single users scenario	Optimised percentages in multi-users scenario
∅	2.03	1.77	1.57	12.31%	22.66%
0.45	2.03	1.82	1.7	10.34%	16.25%

With respect to the practical implementation point of view for the proposed EMS, Table 1 illustrates the evaluating R-users' willingness to utilise the proposed work. In order to analyse the community aspect compared to single R-users optimisation, the same previous R-users load profiles in the scenario without willingness values have optimised their power usage as single-users and community. This implementation method took into account the impact of the individual users' willingness value to the power usage profiles whenever there is a shifting control decision. This decision based on the 10-minutes monitoring of all R-users power usage in the community whether there is or is not a need for shifting. A comparison of results the power usage of R-users who have individually optimised their power usage without considering the power usage of other R-users in the same community is illustrated in Table 1. It is clear that all groups perform better in the community-based solution. This better optimisation is achieved using the energy management algorithm for shifting the load of shiftable appliances. By combining the shiftable power load of all shiftable appliances, then considering peak times of all R-users before taking a shifting decision for each individual appliance of any R-user lead to better PAR results. Empirically, it seems that the community-based solution is the most effective energy management optimisation in all scenarios with and without considering the willingness value of R-users to participate in EMS algorithm. Applying the EMS algorithm in single and multi-users without willingness demonstrates that mostly load profiles of the R-users are optimised.

5. Conclusion

Community-based optimization incorporated into EMS leads to increased optimisation percentages. EMS is a hands-off system supported with optimization algorithms to automatically manage residential users' (R-users) power usage. The end-user has different preferences which could vary based on various factors. However, in previous studies, little attention has been paid to taking into account general uncertainties in the conditions of users. In this study, both EMSs in single users and community-based scenarios have been applied to optimise the power usage of R-users. A system architecture has been proposed to define the composed units which enable the effective performance of EMS.

We found that EMS plays a significant role in power usage optimisation in all tested scenarios of 15 R-users. Regarding the willingness impact to the optimisation results, we found that community-based optimisation performs better and reaches 16.25% which is higher than single users optimisation which only reached 10.34%. These findings indicate that the effectiveness of the proposed EMS optimisation is significant at the point of applying it in single and multi-users scenarios in spite of the variance accepted level of these R-users were considered. Admittedly, modelling the multiplicity conditions of R-users such as time of day, real-time price, and customers' revenue, to find out the willingness value is still an open issue. Future work should, therefore, include follow-up work designed to evaluate whether the willingness values are reflected the vary of multi preferences of R-users in the long term and also whether they continue to be low impact to improve PAR.

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